In search of winning mutual funds in the Chinese stock market

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Abstract

This paper provides a methodological approach, based on the false discovery rate (FDR) of Barras et al. (2010), by which investors can successfully select winning mutual funds and fund managers in China. Our approach allows investors to distinguish between skilled and lucky mutual funds and fund managers and, using this information, to calibrate the proportion of their portfolio funds that are invested in the market index versus funds invested in skilled mutual funds. This feature in our approach can accommodate unique risk appetites and diversification requirements. When accounting for actual transaction costs which individual and institutional investors face in China, we show that our FDR approach can yield positive and economically significant risk-adjusted returns across various rebalancing frequencies. Our approach fares well when compared with naive historical return-based approaches for ranking mutual funds.

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Keywords: Chinese mutual funds; false discovery rate; mutual fund performance.

1. Introduction

Is it possible to select winning mutual funds in the Chinese stock market? In this paper we devise a framework, based on the false discovery rate (FDR) proposed by Barras et al. (2010), to show that, yes, it is possible to select winning mutual funds as well as skilled fund managers. This framework is of direct practical and theoretical importance to portfolio management endeavors and asset pricing at large.

From a practical point of view, we present an innovative FDR method that is empirically tractable with Chinese mutual fund data and whereby parameters that reflect investor holding period horizons, rebalancing frequencies and diversification requirements can be adjusted. From a theoretical point of view, detecting the proportion of skilled versus lucky funds in China and comparing it with what is documented in other developed capital markets contributes to strands of research pertaining to market efficiency and the extent to which informational advantages possessed by select fund managers can be used to "beat the market" (Malkiel, 2007). In all, we present the following four novel and mutually inclusive findings.

Firstly, our FDR approach can accommodate, and be adjusted for, various investor-specific preferences such as holding horizons, rebalancing frequencies and diversification requirements. To accomplish this, we first estimate a Carhart (1997) four-factor model that is specific to Chinese market data and extract alphas for all of our sampled mutual funds (which we hereby refer to as "four-factor alphas"). In order to gauge mutual fund persistence we select funds with positive alphas over the past 24 months and construct 5 equal-weighted and non-overlapping portfolios. These portfolios are arranged based on the significance (*p*-value) of funds' four-factor alphas: p-value $\leq 1\%$, $1\% < p$-value $\leq 5\%$, $5\% < p$-value $\leq 10\%$, $10\% < p$-value $\leq 20\%$ and $20\% < p$-value $\leq 30\%$. The performance persistence of these portfolios is then examined for various holding periods (3, 6, 12 and 24 months, respectively). Using our newly-devised FDR approach, which we explain in more detail later on, we estimate the proportion of funds which are truly skilled (as opposed to lucky) and use this estimate as a method for portfolio allocation and diversification. For instance, if we estimate that 80% of all funds with positive significant alphas are skilled, we form a portfolio whereby 80% of available capital is invested in those funds while 20% is invested in the broad Chinese market index. By investing a portion of their capital in the market index, an investor can add diversification benefits to their portfolio while incurring relatively low transaction fees. In our FDR approach, we show how an investor can dynamically tilt the balance of their portfolio between skilled funds and the market index. This can be achieved by utilizing various *p*-value thresholds within each portfolio. This is an exploitable feature because it gives investors the flexibility to entertain various *p*-value thresholds in selecting truly skilled finds and in accordance with their diversification requirements and risk preferences.[1] This is particularly useful for institutions that invest their clients' money into mutual funds and which must naturally adhere to the specific diversification requirements set by those clients. By thus having the capability to tilt their portfolios between skilled funds and the market, all investors, regardless of size and scope, can maximize the probability that their funds are managed by skilled managers and that they are not overly concentrated into a particular industry or management style.

Secondly, our FDR approach yields risk-adjusted returns (alphas) that are positive and economically significant. This finding, depending on the four-factor alpha *p*-values used to form portfolios, is quite robust across rebalancing frequencies and holds even after accounting for the actual transaction costs which individual or institutional investors must absorb when buying and selling mutual funds in China. This finding is quite remarkable given that the few recent studies investigating Chinese mutual funds collectively conclude that mutual funds and their managers cannot beat the market while those that do are merely lucky and not truly skilled (Yang and Liu, 2015; Yi and He, 2016). Contrary to this perception, however, we show that it is possible to profitably form a portfolio of skilled funds that can be adjusted on the basis of four-factor alpha *p*-values and rebalancing frequencies. The transactions costs used herein, which include purchase and redemption fees, are actual real-world costs which individual and institutional investors face when buying and selling mutual funds in China.

Thirdly, in order to provide a multifaceted view on selecting skilled funds, we apply our FDR approach separately to, first, mutual funds and, second, to fund managers. Treating mutual fund companies and mutual fund managers as two separate 'units' for empirical analysis is important because fund managers, for whatever reasons, may switch employment between competing mutual fund companies. Decoupling the two is also important because mutual fund companies may have 'star' managers who, relative to their whole team, disproportionately contribute to their company's stellar performance but who may, at any time, leave to join another company. From our FDR approach, we show stronger evidence of outperformance persistence at

[1] As we illustrate later on, investors are free to choose whatever *p*-value thresholds they wish and not necessarily those entertained in our paper.

the fund manager level relative to the whole mutual fund company level. This indicates that individual fund managers who are 'stars' contribute disproportionately more to their company's outperformance in relation to their fund management team. In our analysis we decouple fund managers from fund companies and implement our FDR approach across four-factor alpha *p*-values and rebalancing frequencies. We show that our approach can be used for selecting winning fund managers and, therefore, winning fund companies. In fact, depending on the four-factor alpha *p*-values and rebalancing frequencies used, a portfolio strategy of fund selection using our FDR approach whereby fund managers are the 'unit' of measurement yields positive and economically significant risk-adjusted returns (alphas) that are relatively greater compared to when mutual fund companies are used as the 'unit' of measurement. Thus, from a practical perspective, employing our FDR approach empowers investors to select truly skilled fund managers in an industry where 'star' managers actively switch employment between competing mutual fund companies. From a theoretical managerial perspective, our findings lend credence to the adage that *employees are a company's greatest asset* - albeit, in our case, *fund managers are a mutual fund company's greatest asset*. As in the previous findings, this finding also holds in the presence of actual real-world transaction costs in China.

Fourthly, we examine how our FDR approach fares in relation to naive return-based approaches for ranking mutual funds. In China, there is a growing number of investment and trading websites, such as *Sina Finance, Howbuy* and *Cnstock*, which provide buy, hold and sell recommendations for mutual funds depending on their past returns.[2] These websites are closely watched by Chinese investors and are gaining popularity. The question is, do their historical return-based approach for ranking funds provide investors with useful information that they can exploit to earn superior risk-adjusted returns? We investigate this and show that their return-based methods of ranking funds yields poor risk-adjusted returns relative to our FDR strategy. It may be the case that these types of websites are providing rankings that are consistent with the behaviors of feedback traders - this is because we show that past winners do not reliably yield future positive and significant four-factor alphas. It may well be the case that such past winning funds were lucky and, therefore, experience mean reversion in their future performance.

[2] The URLs for these websites are as follows: finance.sina.com.cn (*Sina Finance*), www.howbuy.com (*Howbuy*) and www.cnstock.com (*Cnstock*). These Chinese websites are, to some extent, comparable to the US version of Jim Cramer's *Mad Money* (www.thestreet.com) which is used by investors to get buy, hold and sell recommendations on various stocks and funds.

Taken together, our findings can benefit practitioners while serving to further theoretical discussions on market efficiency. Given the tractability of our FDR approach with Chinese market data and the ability to adjust the strategy on the basis of investor diversification requirements and rebalancing frequencies, market practitioners can automate and operationalize the approach we posit herein to select winning funds or fund managers in China's unchartered mutual fund industry. Institutional investors are especially positioned to benefit given the lower transaction costs they face when executing trades. Theoretical discussions on market efficiency also benefit from our findings. From our analysis, we echo the findings of recent studies which show that Chinese mutual funds on aggregate cannot generate statistically significant positive returns beyond what is predicted by the Carhart (1997) four-factor model. However, when using our newly devised FDR approach, we show that approximately 7% of Chinese stock funds exhibit true stock selection abilities - a proportion that is relatively higher than what is observed in developed markets (Cuthbertson and Nitzsche, 2013). This finding provides support for Malkiel (2007) who argues that China's stock markets are weak-form efficient relative to other developed markets and suggests that Chinese fund managers can, relative to fund managers domiciled in developed markets, better exploit any information advantages they may possess.

These findings contribute to the various strands of academic literature which either explore the empirical usefulness of alpha as a measure of fund performance (Chung et al., 2015) or which implement conventional technical strategies often used by practitioners in order to predict mutual fund returns (Sapp, 2011). They also contribute to studies that dissect the various determinants of managers' buying and selling decisions and the extent to which such decisions affect overall fund performance (Ferruz et al., 2010; Rohleder et al., 2017; Tosun, 2017; Popescu and Xu, 2018; Wang and Yu, 2018). In addition, our implementable framework for selecting winning mutual funds is a response to the findings by Chang et al. (2003) and Rahman et al. (2017) who argue that there are limitations associated with solely using Jensen's alpha as a tool for evaluating and detecting performance characteristics in the mutual fund industry.

We structure the remainder of our paper as follows. In the second section we provide a background discussion of motivational literature and some characteristics that set apart China's mutual fund industry from that of other developed markets. In the third section, we discuss our estimation procedure. The fourth section discusses the nature of our data. The fifth section reports on the general performance of Chinese mutual funds. The sixth section outlines our FDR trading strategy. The seventh section concludes.

2. Motivation and Literature Review

There is a growing abundance of mutual funds today that can satiate the expected risk-return preferences of virtually any type of investor.[3] At least two fundamental forces have fuelled this growth; the first is rooted in investor psychology and detailed by Shiller (2015) who, through survey evidence, finds that although investors lack confidence in selecting stocks themselves, they seem more confident in their abilities to select successful fund managers who can themselves pick winning stocks.[4] The second is the byproduct of the rapid globalization we have experienced in the last few decades. As nations continue to liberalize their capital markets and decrease trade barriers, individual and institutional investors in mature markets increasingly seek to diversify their assets or adjust the expected risk-return characteristics of their portfolios by investing in emerging markets through actively managed mutual funds (Gelos, 2011).

In recent years, those investors seeking to capitalize on growth opportunities in emerging economies have eagerly gravitated to China.[5] This is not surprising given that it is currently the world's second largest economy in terms of market exchange rates and, from 2000 until 2015, China has accounted for approximately one-third of global economic growth (Arslanalp et al., 2016). The Chinese government has sought to support policy initiatives to sustain the influx of foreign investment into its borders and to attract investors into its capital markets. Thus, in the last two decades, it has passed various liberalization measures that make its capital markets more accessible to outside investors. For example, in 2001 China gained accession to the World Trade Organization (WTO) which then allowed its financial institutions to issue bonds in international markets. In 2002, China passed the qualified foreign institutional investor (QFII) program which allows qualified global institutional investors to purchase RMB-denominated A-shares in its

[3] According to the Investment Company Institute (ICI), the total net assets of all mutual funds around the world is estimated to be $40,364,115 (in millions of US dollars) as of the 4th quarter of 2016. Some key worldwide market data statistics on mutual funds is publicly available at *https://www.ici.org/research/stats/worldwide*.
[4] See the survey results and an accompanying discussion of the questionnaire he gave to participating individual investors on page 220 of Shiller (2015).
[5] According to the United Nations Conference on Trade and Development (UNCTAD), China currently ranks third in the world as the largest foreign direct investment (FDI) recipient to the United States and Hong Kong; see figure I.4. on page 5 of UNCTAD's 2016 World Investment Report: *http://unctad.org/en/PublicationsLibrary/wir2016_en.pdf*.

Shanghai and Shenzen stock exchanges. In similar spirit with QFII, the qualified domestic institutional investor (QDII) program, passed in 2006, allows qualified domestic institutional investors to invest in foreign-based asset securities.

The combination of China's explosive economic growth coupled with its liberalization initiatives have thus attracted many outside "western" investors seeking to boost their portfolio exposure to China via mutual funds. These investors, however, need to appreciate the vital dissimilarities between China's mutual fund industry with that of other developed nations in order to better manage their risks and to make more informed decisions.

Firstly, the investment duration in Chinese mutual funds is relatively short compared to investment durations in mutual funds domiciled in other developed markets. For example, in the Shanghai and Shenzhen stock markets, it was estimated that about 60% to 80% of QFII investors maintained a holding period duration of 3 to 12 months while 20% to 40% of these types of investors held for less than 3 months.[6] Secondly, mutual fund turnover ratios in China are several times higher than the turnover ratios observed in other developed markets; for example, in 2007, which was a bull period in China and international stock markets, the turnover ratio was estimated to be in excess of 900% while turnover ratios are typically below 200% for other developed markets.[7] Finally, unlike in other developed markets, the majority of domestic institutional investors who actively buy and sell mutual funds are investment firms while other markets see more equal representation among investment firms, insurance companies and pension funds.[8] This has led the China Securities Regulatory Commission (CSRC, 2008) to caution market participants by stating that "...existing institutional investors are too homogeneous in their investment strategies and investment pools, which could be detrimental for the long-term development of China's stock markets..." (p. 272).

These characteristics are important for outside investors to understand because, unlike in developed markets, this "short-termism" in investment behavior - as Yuan et al. (2008) describe it

[6] These are approximate figures estimated in 2007 by the China Securities Regulatory Commission (CSRC). See figure 3.21 on page 270 of the China Capital Markets Development Report published in 2008 by the CSRC (2008). While updated versions of this report have yet to circulate, the 2008 report is available online: *https://openknowledge.worldbank.org/handle/10986/12643*. In our analysis, we entertain various rebalancing frequencies that are consistent with these holding period durations.

[7] These are approximations. See figure 3.23 on page 272 of the China Capital Markets Development Report published by the CSRC (2008). Footnote (4) provides a URL link to this report.

[8] See figure 3.24 on page 273 of the China Capital Markets Development Report published by the CSRC (2008). Footnote (4) provides a URL link to this report.

- can make it difficult for sharp-penciled investors to use a strategy for measuring and ranking the performance of mutual funds.

The FDR approach we propose provides a solution to this challenge and is advantageous because it is adjustable on the basis of diversification requirements or rebalancing frequencies. In this paper we also show how empirically tractable our FDR approach is to Chinese market data.

Thus far, extant literature focuses on developed markets in order to determine whether mutual funds can beat the market (Elton et al., 1993; Chen et al., 2000; Wermers, 2000). Others examine the persistence in mutual fund performance to determine whether this can be used to identify winning funds (Grinblatt and Titman, 1992). Hendricks et al. (1993) documents a "hot hand" versus "ice hand" phenomena - specifically, funds that were winners (losers) in the last four quarters perform significantly better (worst) than the average. Brown and Goetzmann (1995) utilize a database that is free of survivorship bias and document relative risk-adjusted performance. Carhart (1997) proposes a four-factor model and argues that persistence in mutual fund performance is merely the consequence of the momentum effect documented by Jegadeesh and Titman (1993).

Other authors propose various econometric frameworks for distinguishing lucky funds from those that are truly skilled. Kacperczyk et al. (2005) find that industry-concentrated fund managers tend to have more investment ability than managers who prefer to diversify. Kosowski et al. (2006) apply a bootstrapping method and show that the performance of the best and worst fund managers cannot be explained solely by sampling variability - implying that the best performing managers are not merely lucky and some of them do possess stock selecting abilities. In addition, they observe short-term persistence over one year in the top decile when ranking on past 36-month alphas. Using the same method, Cuthbertson et al. (2008) examine mutual funds in the UK and conclude that the top performing funds may have stock selection abilities while the low performing funds are just unlucky. Fama and French (2010) use another bootstrapping simulation to examine mutual fund performance and find there are only few funds that can generate positive risk-adjusted returns while Kacperczyk et al. (2014) show that skilled managers show stock selection abilities in bull markets and market timing abilities during bear markets.

In recent years, the FDR methodology proposed by Barras et al. (2010) is beginning to be explored more as a tool for distinguishing skilled funds from those that are lucky. Their study, which examines US mutual funds, suggests that almost no fund is truly skilled over the whole sample period. However, they do find that approximately 2.5% of equity funds are truly skilled over a 5-year period. Furthermore, they find positive persistence for the top performing funds (when FDR=10%)[9].

The advantage of FDR as a baseline model is that it allows us to know what proportion of funds are skilled versus lucky. By using this method, Cuthbertson et al. (2012) find only 3.7% of UK mutual funds are skilled but find no evidence of performance persistence. In the German mutual fund industry Cuthbertson and Nitzsche (2013) demonstrate that at most 0.5% of mutual funds are skilled while in the Australian mutual fund industry Kim et al. (2014) find about 27% of funds have significantly positive true alphas.

Research on China's mutual fund industry is relatively scant thus far despite the rapid growth in assets under management (AUM) by mutual funds.[10] Collectively, the literature on Chinese mutual funds concludes that, firstly, fund managers cannot beat the overall market and, secondly, those that do beat the market are lucky and not truly skilled (Zhang and Du, 2002; Zhuang and Tang, 2004; Wermers and White, 2006; Yang and Liu, 2015; Yi and He, 2016; Yi and Hu, 2016).

3. Methodology

3.1 Measurement of Fund Performance

To measure mutual fund performance, we use the four-factor asset pricing model proposed by Carhart (1997):

$$r_{i,t} - r_{f,t} = \alpha_i + b_i \cdot RMRF_t + s_i \cdot SMB_t + h_i \cdot HML_t + m_i \cdot MOM_t + \varepsilon_{i,t} \qquad (1)$$

where $r_{i,t}$ is the return of fund i in month t; $r_{f,t}$ is the risk-free rate, which is proxied by the 1-year fixed deposit rate (expressed in monthly terms) in month t; $RMRF_t$ is the excess return of monthly

[9] According to Barras et al. (2010), the larger the value for FDR, the more likely it is lucky funds will be included in the test portfolio. Thus, an empiricist faces a tradeoff: a large FDR will grant a larger sample of high performing funds but with a higher likelihood of that sample including lucky funds. On the flipside, a lower FDR decreases the sample but increases the likelihood that the selected funds are truly skilled and not lucky. This is discussed more in the methodological section of our paper.

[10] Since 2001 when the first mutual fund was established, there has been an explosion of funds available in China for investors. As of 2014, the assets under management (AUM) of fund management companies' segregated accounts rose to 1.2 trillion RMB (CSRC, 2014).

aggregated market portfolio in month t and SMB_t, HML_t and MOM_t are the month t returns on zero-investment mimicking portfolios of size, value and momentum factors, respectively. The market portfolio is value-weighted where the weights are based on their market capitalization of tradable shares. As we focus on the stock funds and stock-dominated hybrid funds that invest domestically, the market portfolio only involves A-shares that traded in both Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE).

Size and value factors are constructed following Hu et al. (2018) whereby we construct six double-sorted portfolios to mimic the size and value risk factors proposed by Fama and French (1993) for the Chinese stock market. Specifically, at June of year t, we sort all non-financial stocks traded in the SSE and SZSE based on their size.[11] We then divide these stocks equally into two groups; namely big and small. Stocks with a size greater than or equal to the median are in the big group while stocks with a size smaller than the median are in the small group.

In the same way, at June of year t, we construct three value-sorted portfolio based on each stock's book-to-market ratio at December of the previous year ($t-1$) whereby cutting points are the 30th and 70th percentiles, respectively. We then intersect two size-sorted portfolios with three value-sorted portfolios and this yields six portfolios (Small Value, Small Neutral, Small Growth, Big Value, Big Neutral and Big Growth). We then proceed to calculate monthly value-weighted average returns from July of year t to June of year $t+1$ and these six portfolios are rebalanced at June of each year. The size and value risk factors are mimicked by the following two portfolios (small minus big and high minus low):

$$SMB = \frac{(Small\,Value + Small\,Neutral\, + Small\,Growth)}{3} - \frac{(Big\,Value + Big\,Neutral\, + Big\,Growth)}{3} \tag{2}$$

$$HML = \frac{(Small\,Value + Big\,Value)}{2} - \frac{(Small\,Growth + Big\,Growth)}{2} \tag{3}$$

[11] Size is defined as the market capitalization of tradable A-shares. In China, domestic A-shares are divided into tradable A-shares (which are also called floating A-shares or negotiable A-shares) and non-tradable A-shares. Non-tradable shares are typically held by the government and cannot be traded in the stock market (Firth et al., 2010). Hence, following Hu et al. (2018), in this paper we use the market capitalization of tradable A-shares when measuring firm size.

Similarly, we construct the momentum factor with the methodology described in Kenneth French's data library by constructing winner and loser portfolios.[12] At each month, all non-financial stocks are sorted by their previous 11-month buy-and-hold returns. We then define the top 30% as winner stocks and the bottom 30% as loser stocks. Hence, the momentum factor is constructed as the value-weighted average returns of winners minus the value-weighted average returns of losers where weights are the market capitalization of tradable shares.

Finally, it is important to note that mainland Chinese stock markets experience more frequent trading suspensions than what is typically observed in developed stock exchanges. This idiosyncrasy, however, is not a major concern for our methodology and our findings because we are using monthly return data and it is very rare for a suspension to last more than an entire month. From our total sample pool of stocks for each month, only 1.3% experienced a trading suspension of more than an entire month.[13] In addition, it is important to note that our four constructed pricing factors in equation (1) yield an R-squared value of approximately 94%, which is comparable to that of Hu et al. (2018).

3.2 Measurement of Luck

We apply the FDR approach proposed by Barras et al. (2010) to measure the impact of luck on mutual funds' performance. Their approach classifies the entire fund population into three categories: Unskilled funds (π_A^-), zero-alpha funds (π_0) and skilled funds (π_A^+), respectively. Unskilled funds are funds with statistically significant negative estimated alphas and "true" negative alphas ($\hat{\alpha} < 0$ and $\alpha < 0$). These fund managers do not possess stock selection skills to cover their management fees, transaction costs and other expenses.

Skilled fund managers are those who have the ability to select stocks that can not only recover all the fees and costs, but also provide a surplus to investors. These funds have both statistically significantly positive estimated alphas and positive "true" alphas ($\hat{\alpha} > 0$ and $\alpha > 0$). The three crucial elements of the FDR approach are, firstly, the zero-alpha funds, which involve lucky funds (funds with significantly positive estimated alpha but zero "true" alpha, i.e., $\hat{\alpha} > 0$ but $\alpha = 0$). Secondly, the unlucky funds (funds with significantly negative estimated alpha but

[12] See the methodology here: *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html*.

[13] More details are available upon request. Adjusting for trading suspensions is not common practice in asset pricing tests of the Chinese stock market (e.g., Lu et al., 2017; Hu et al., 2018).

zero "true" alpha, i.e., $\hat{\alpha} < 0$ but $\alpha = 0$). Thirdly, the funds with insignificant estimated alpha ($\hat{\alpha} = 0$ and $\alpha = 0$). Once we know the proportion of zero-alpha funds, we can easily conjecture the probability of zero-alpha funds being lucky and unlucky with respect to the selected significance level. Subtracting the proportion of funds with significantly positive estimated alpha by the percent of lucky funds, we end up with the proportion of skilled funds with positive "true" alphas. We can obtain the proportion of unskilled funds in the same way. Specifically, the proportion of unskilled funds can be computed by subtracting the proportion of funds with significantly negative estimated alpha by the proportion of unlucky funds, which should belong to the zero-alpha fund population.

Compared to other methodologies, the FDR approach allows us to know the proportion of fund managers who possess "true" skill to select stocks and where these funds are located in the estimated alpha distribution. Another attractive attribute of this approach is its empirical simplicity. The only parameter that needs to be estimated is π_0 (the proportion of zero-alpha funds). The estimation procedure is discussed in the following subsection.

3.2.1 Estimation Procedure

The first step is to estimate the proportion of zero-alpha funds in the fund population. Since skilled and unskilled funds both have *p*-values that are extremely close to zero, we are able to exploit this attribute to make inference about the proportion of zero-alpha funds.[14] After selecting a sufficiently large *p*-value, we can conjecture that funds with *p*-values greater than the selected threshold (λ^*) come from the zero-alpha fund population. Figure 1 demonstrates this idea graphically.

(Insert Figure 1)

In figure 1, we select an intermediate level of λ^* (0.6).[15] The bars that are lighter grey, which are on the right hand side of the dashed line, represent funds with *p*-values greater than the selected

[14] In the rest of this paper, *p*-values refer to the *p*-values of alpha estimated by the Carhart (1997) four-factor pricing model in equation (1) under the null hypothesis that the estimated alphas are not different from zero.
[15] To select λ^*, Barras et al. (2010) use the bootstrapping method proposed by Storey (2002) to minimize the mean squared error of $\hat{\pi}_0$ and argue that empirical results are not sensitive to the selection of λ^*. Hence, we fix the value of λ^* to 0.6 throughout our paper.

threshold (i.e., these funds are zero-alpha funds). These proportion of funds in the light grey area can be expressed by the following equation:

$$\hat{P} = \frac{\widehat{W}(\lambda^*)}{M} \tag{4}$$

whereby $\widehat{W}(\lambda^*)$ are the number of funds with estimated *p*-values greater than λ^* and M equals the total number of funds in our sample.

Furthermore, as shown in figure 1, the interval between 0.5 and 1 roughly presents a uniform mass. Hence, zero-alpha funds can be assumed to be uniformly distributed (Barras et al., 2010). In other words, funds that are under the solid line are zero-alpha funds (π_0) and funds over the solid line are skilled funds (π_A^+) plus unskilled funds (π_A^-). Hence, given a selected λ^*, we have the proportion of zero-alpha funds approximately equivalent to:

$$\hat{\pi}_0 = \frac{\hat{P}}{(1-\lambda^*)} = \frac{\widehat{W}(\lambda^*)}{M} \cdot \frac{1}{(1-\lambda^*)} \tag{5}$$

whereby $\hat{P}$ is presented in equation (4) and λ^* is the selected level of the threshold.

After estimating $\hat{\pi}_0$, the distribution of the zero-alpha fund population is assumed to be normal with zero mean for simplicity. Hence, funds in the left tail represent unlucky funds that have significantly negative estimated alphas but zero "true" alphas. Similarly, funds in the right tail represent lucky funds that have significantly positive estimated alphas but zero "true" alphas. Thus, we have the following:

$$\hat{F}_\gamma^+ = \hat{F}_\gamma^- = \hat{\pi}_0 \cdot \frac{\gamma}{2} \tag{6}$$

whereby γ is the pre-determined significance level.

Finally, subtracting the proportion of funds with significantly positive alpha ($\hat{S}_\gamma^+$) by the proportion of lucky funds ($\hat{F}_\gamma^+$), we end up with the proportion of truly skilled funds $\hat{T}_\gamma^+$. We can also obtain the proportion of unskilled funds, $\hat{T}_\gamma^-$, the same way:

$$\hat{T}_{\gamma}^{+} = \hat{S}_{\gamma}^{+} - \hat{F}_{\gamma}^{+} = \hat{S}_{\gamma}^{+} - \hat{\pi}_0 \cdot \frac{\gamma}{2} \tag{7}$$

$$\hat{T}_{\gamma}^{-} = \hat{S}_{\gamma}^{-} - \hat{F}_{\gamma}^{-} = \hat{S}_{\gamma}^{-} - \hat{\pi}_0 \cdot \frac{\gamma}{2} \tag{8}$$

4. Data

All the data that are used in this study are collected from the China Stock Market and Accounting Research (CSMAR) database complied by GTA Information Technology Co., Ltd., which is one of the largest financial data vendor in China. We use several criterion when obtaining our sample funds and fund managers. Firstly, since we focus only on the performance of actively managed open-end equity funds that solely invest in mainland China, we exclude bond funds, money market funds, fund of funds, index funds, index futures funds and QDII funds that invest globally. To ensure that the Carhart (1997) four-factor model is a valid benchmark for hybrid funds, we only include stock-dominated funds and delete the rest.[16]

Secondly, because the four-factor model needs a relatively long period of data to provide accurate estimation, all funds that are involved in our sample must have at least two years of monthly return data.

Thirdly, the first mutual fund in China was launched in 2001 and, during this stage, there were too few funds that could be used to draw inferences. Since the FDR method cannot feasibly be executed when the sample size is too small, our sampling period is from January 2007 until December 2015. This sampling period is the same with that used when sampling fund managers in order to test whether it is possible to distinguish luck from skill in fund manager performance (given that fund managers may switch employment from one fund company to another).

These aforementioned criteria, when applied, yield a sample consisting of 235 unique mutual funds and 400 fund managers. Note that our fund sample is free from survivorship bias. Up until December 2015, there was no actively managed open-ended fund that liquidated - although there were some exchange traded funds (ETFs) liquidated. Though our fund sample is

[16] We define stock-dominated hybrid funds as funds that maintain an average stock-holding proportion greater than 70% throughout the sample period.

free from survivorship bias, we should remind readers that we cannot guarantee there is no survivorship bias in our fund manager sample because fund managers who have extremely bad short-term performance may be fired immediately.

Fund unit splits and cash dividends may cause jumps in fund net asset values (NAV) and, consequently, NAV returns. Since the NAV returns provided by CSMAR are not adjusted for unit splits or cash dividends, we perform the following adjustment directly as follows:

$$r_{i,t} = \frac{NAV_{i,t} \cdot Split_{i,t} + D_{i,t} - NAV_{i,t-1}}{NAV_{i,t-1}} \tag{9}$$

whereby $r_{i,t}$ is fund i's split- and dividend-adjusted return in month t; $NAV_{i,t}$ is fund i's net asset value per unit in month t while $NAV_{i,t-1}$ is the net asset value per unit in the previous month; $Split_{i,t}$ is the split ratio of fund i in month t and $D_{i,t}$ is the cash dividend of fund i in month t. All fund fees (except for the initial purchase fee and redemption fee) and expenses (such as transaction costs) have been deducted from fund NAVs already. Hence, the advantage of using NAV return is that we can obtain a net-of-fee return.

5. Fund Performance and the Impact of Luck

5.1 Aggregate Performance

We first examine Chinese mutual fund performance at the aggregate level. To test the aggregate performance, we construct equal- and value-weighted portfolios which involve all available funds at month t. For the value-weighted portfolios, specifically, weights consist of each fund's total assets under management reported in December of the previous year. Then we estimate the four-factor model for these two portfolios across the sample period (January 2007 to December 2015) to see whether there exist significant alphas.

(Insert Table 1)

Panel A of table 1 reports the aggregate performance of the equally-weighted portfolio. The estimated monthly alpha of the equally-weighted portfolio is 0.13% but is not statistically significant with its *p*-value of 0.4772. Panel B of table 1 demonstrates the monthly performance of the value-weighted portfolio at the aggregate level. Compared to the equally-weighted portfolio, the monthly alpha of the value-weighted portfolio is even lower and statistically insignificant as well. This implies that funds that are smaller in size may perform better than those which are bigger. Chen et al. (2004) argue that the significant negative impact of size on fund performance is possibly due to liquidity and organizational diseconomies. Gong et al. (2016) confirm this relationship in the Chinese mutual fund market by providing evidence that fund performance decreases when there are multiple large shareholders present.

The results of both the equally- and value-weighted portfolio indicate that, on average, Chinese mutual funds cannot provide positive abnormal returns that are beyond what the four-factor benchmark predicts. From an investor's perspective, these results indicate that actively managed mutual funds in the Chinese stock market may be no better than simply investing in a broad market portfolio.

5.2 Performance of Randomly Selected Funds

In addition to the equally- and value-weighted portfolios, we then construct a portfolio with randomly selected funds to examine the general performance of actively managed equity funds. This random-selection strategy may reflect the actual fund selection strategy taken by investors who are lack knowledge in mutual funds and investing at large. We test the performance of the random-selection trading strategy by using different holding periods (3 months, 6 months, 12 months and 24 months). These holding periods are consistent with the actual holding periods of QFII investors who trade in the SSE and SZSE (see footnote (4) and its associated discussion).

At the beginning of each holding period, we rebalance these portfolios by randomly selecting 5 funds which are available at that month. Then we calculate the equally-weighted average monthly return of this randomly selected portfolio.

(Insert Table 2)

Table 2 shows the performance of the randomly selected portfolios. Specifically, monthly estimated alphas are 0.09%, 0.08%, 0.07% and 0.01% with 3-month, 6-month, 12-month and 24-month holding periods, respectively. As expected, none of these alphas are significantly different from zero, which is consistent with the results presented in table 1 as well as the aforementioned extant literature we discussed.

It is worth noting that these alphas do not account for transaction costs or redemption fees. This means that if investors really do engage in random selection behavior, they more likely will be left with a negative alpha portfolio of mutual funds. Fund purchase fees are approximately 1.5% per transaction for individual investors who do not buy large blocks of shares as do institutional investors.[17] Individual investors who thus do not possess mutual fund selection abilities likely will not generate sufficient returns to cover their risks or the fees which companies charge.

5.3 Skilled Fund Proportion

As demonstrated by Barras et al. (2010) and Kosowski et al. (2006), even though the general performance of actively managed funds is poor, there still exists a small proportion of funds which are truly skilled. Following Barras et al. (2010), we thus use the FDR approach to detect whether there are some skilled funds in China. For each fund, we estimate its alpha and the corresponding *p*-value using equation (1) from the fund inception month until December 2015. We then estimate the proportion of skilled funds using the procedures described in Section 2. As demonstrated by Barras et al. (2010), the estimation procedure is not sensitive to the selection of λ^*. However, for robustness purposes, we select three different values of λ^* to evaluate the impact of luck on the performance of Chinese mutual funds.

(Insert Table 3)

Panels A, B and C of table 3, respectively, report the proportion of skilled funds and unskilled funds in the entire fund population with λ^* of 0.5, 0.6 and 0.7, in each panel. For example, at the significance level of 10% ($\gamma = 0.1$) and λ^* equals to 0.6, we observe that there are around 7% of all actively managed funds that are skilled and only 0.2% which are unskilled. Compared to the findings in developed countries such as the US and UK, it appears that mutual funds in China exhibit a larger proportion of skilled funds. This may not be surprising given that the SSE and SZSE are weak-form efficient relative to other developed markets and thus more

[17] Fund purchase fee typically decreases as the amount of purchase increases. For individual investors who normally invest less than 1 million RMB, the purchase fee is around 1.5%. For more information, please see the transaction cost subsection (6.1.1).

arbitrage opportunities exist and informational advantages are relatively more lucrative to trade on (Malkiel, 2007). Consistent with Barras et al. (2010), the results reported in these three panels are robustly similar across different values of λ^*.

6. Trading Strategy

Having established that there is a small proportion of funds that are truly skilled, the next step is to determine how an investor would identify such funds. While the FDR approach only allows us to understand what proportion of funds are skilled, we do not know which individual funds specifically are skilled.

It is possible, however, to rationally predict which funds are skilled according to their estimated *p*-values. Funds with smaller estimated *p*-values are more likely to come from skilled and unskilled funds (Barras et al., 2010). Hence, for funds with positive estimated alphas, if we sort them on the basis of their estimated *p*-values, the smaller the estimated *p*-value is the higher the probability that these funds coming from the population of skilled funds.[18] Another advantage of ranking funds on the estimated *p*-values is that, compared to ranking funds on estimated alpha itself, ranking funds on the estimated *t*-statistics are able to control for the heterogeneity in risk-taking across funds (Kosowski et al., 2006).

6.1 Trading Strategies for the Leading Funds

We first examine performance persistence for different fund portfolios, which are formed based on their estimated *p*-values. To test funds' performance persistence, we construct 5 equally-weighted portfolios on the basis of estimated *p*-values. Furthermore, we rebalance these portfolios at different frequencies including 3, 6, 12 and 24 months, respectively, to see during what time horizon funds show evidence of performance persistence.

To accomplish this, and for each holding period, at the start of each holding period, we estimate a four-factor alpha and extract its corresponding *p*-value for each fund based on its previous 24-month performance. For funds with positive estimated alphas, we then construct 5

[18] The reason that we do not focus on the persistence of past poor funds is that almost all of the Chinese mutual funds cannot be shorted due to short selling constraints. Hence, knowing the persistence of past poor funds cannot actually help investors to develop fund selection strategies.

equally-weighted portfolios based on their estimated *p*-values (*p*-value ≤ 1%, 1% < *p*-value ≤ 5%, 5% < *p*-value ≤ 10%, 10% < *p*-value ≤ 20% and 20% < *p*-value ≤ 30%). We then hold these 5 portfolios for different periods (3, 6, 12 and 24 months) and, using the four-factor model, evaluate their performance based on the monthly return data during each of the holding periods.

We test our trading strategies during the entire sample period from January 2007 to December 2015. For portfolios with a rebalancing frequency between 3 and 12 months, the first portfolio is formed at January 2007. For portfolios with a 24 month rebalancing frequency, the first portfolio is formed in January 2008.

(Insert Table 4)

The second column of table 4 reports the performance of these 5 portfolios. Empirically, we observe that funds in the extreme right tail exhibit short-term performance persistence up to one year, which is consistent with the findings of Bollen and Busse (2005).[19] For instance, in panel A, the portfolio that includes funds with past estimated *p*-value smaller than 1% yields significant positive monthly alphas of around 0.7% and 1% for the 6- and 12-month holding periods, respectively. Funds with past estimated *p*-values greater than 1% and smaller than 5% provide significantly positive monthly alphas of about 0.54% and 0.45% for the 3- and 6-month rebalancing frequency, respectively. For funds with past estimated *p*-values greater than 5%, we do not observe any superior performance than what can be explained by the four-factor model.

As mentioned, some of the funds with significantly positive alphas might be the result of luck. Carrying "lucky" mutual funds in one’s portfolio and expecting such performance to persist is a precarious strategy since these funds are most likely to experience mean reversion. Hence, in order to improve the performance of these portfolios, we also take the impact of luck into consideration. Specifically, at the beginning of each holding period, we estimate the proportion of skilled funds in each portfolio using the FDR method described in section 3 based on the previous 24-month data:

$$Skill\_Pct = \frac{T_{\gamma}^{+}}{S_{\gamma}^{+}} \tag{10}$$

[19] They estimate standard stock selecting and market-timing models using daily mutual fund data and find short-term persistence.

where T_γ^+ is the number of skilled funds; S_γ^+ is the number of funds with significantly positive estimated alphas and γ is significance level.

At this stage of the analysis, we are cognizant of the negative effects which "lucky" funds can have on the long-term performance of our portfolio. We instead want to include "skilled" funds into our portfolio as this increases the probability that we will be profitable (we thus want to have a high percentage of skilled funds, $Skill\_Pct$, at any given period).

On this basis, and keeping in mind that it is in investors' interests to be able to maintain a portfolio of skilled funds while simultaneously diversifying, we formulate our FDR strategy as follows. If, for example, 80% of all funds with significantly positive alphas are skilled, 80% of all available cash will be invested in the top fund portfolio while 20% of available cash will be invested in the market index fund. By doing so, investors can maintain some level of diversification while also reducing their exposure to management fees which actively managed funds charge. The FDR portfolio is thus the weighted-average of the leading fund portfolio and the passively managed market index fund (Hushen 300 ETF) where the weight is exactly the skilled fund percent ($Skill\_Pct$).[20]

The third column of table 4 reports the performance of our FDR trading strategy. In panel A, our FDR strategy cannot outperform because most of funds in this portfolio are truly skilled and their performance is highly persistent. However, from Panel B to Panel E, the FDR strategy outperforms for most of the time. For instance, in panel B, the FDR strategy provides monthly alphas of approximately 0.62%, 0.57% and 0.52% for 6-, 12- and 24-month rebalancing frequencies, respectively. Even for groups with *p*-values greater than 10% (shown in panels C, D and E), we observe significantly estimated alphas for 6- and 12-month rebalance frequencies. Even though the FDR strategy cannot beat the most skilled fund portfolio, it is also well worth noting that our FDR approach helps investors diversify their fund portfolios and improve performance simultaneously. It is not always possible that the best performer portfolio (panel A in table 4) would fulfill investors' diversification requirements (only 3 or 4 funds in the portfolio). As a consequence, if investors need more funds in their portfolios, the FDR strategy is able to help them improve the performance of higher *p*-value groups (Panel B to Panel E) significantly.

[20] The Hushen 300 ETF is the most popular index ETF in China and is highly liquid. The Hushen 300 ETF was first introduced in May 2012 while, prior to this date, the Hushen 300 ETF in our FDR strategy is replaced by the Shangzheng 50 ETF.

By including an adjustment for luck, our FDR trading strategy performs better than the leading fund trading strategy. Naturally, the lowest *p*-value applies the strictest criteria and results in the highest *Skill_Pct*. This is shown in the last column of panel A where *Skill_Pct* is 83%, 82%, 78% and 92% for the 3-, 6-, 12- and 24-month rebalancing frequencies. Operationalizing our strategy would thus entail investing at least 80% of available capital in these skilled funds in order to maximize an investor's rate of return.

Skill_Pct decreases as the estimated past *p*-values increases (the threshold becomes more relaxed). In panel E, only 10% of funds in that portfolio are skilled, suggesting that at this level there are many funds that are lucky. Investors need to be wary of such funds because they will most likely result in poor performance in the future.

6.1.1 Transaction Costs

One important test a trading strategy is whether it is still able to provide significantly positive alphas even in the presence of transaction costs. In this section, we subtract the monthly return of the 5 equally-weighted portfolios by the corresponding monthly trading cost and then re-estimate the performance of our trading strategies.

Fund purchase fees vary significantly with respect to investment amount. For instance, an investment of less than 500,000 RMB incurs a charge of 1.5% of the investment amount. For an investment greater than 10 million RMB, the investor is charged at about just 1,000 RMB per transaction. The structure of fund purchase fees motivates us to evaluate transaction cost-adjusted performance for individual and institutional investors separately because institutional investors benefit from economies of scale. Hence, for individual investors, we set a purchase fee of 1.5% while for institutional investors the purchase fee is set at 0.04%.[21]

Redemption fees vary with the holding period instead of the investment amount. However, under our trading strategies, investors will hold funds for the short-term (no longer than 2 years). As a consequence, we set the common redemption fees at the short-term rate of 0.5% for both individual and institutional investors. The Hushen 300 ETF is used as a market portfolio for money that is not invested in skilled mutual funds. The buying and selling costs of this ETF per transaction

[21] *Howbuy.com* provides fee information for individual funds. For more information about purchase and redemption fees, please use the following URL link: *https://www.howbuy.com/fund/*.

typically do not exceed 0.25%.[22] Thus, we set the buy and sell costs at 0.25% for both individual and institutional investors.

(Insert Table 5)

Table 5 reports the transaction cost-adjusted performance of our trading strategies for individual investors. As shown, the performance decreases dramatically after incorporating transaction costs. For the leading fund strategy, both estimated alphas and significance levels decrease sharply; as reported by the second column, for the first portfolio with lowest past *p*-value funds, it provides a significantly positive alpha only during the rebalancing frequency of 12 months. The other positive abnormal returns are also eroded by transaction costs; for panels C and D, we now observe negative alphas for the 3-month rebalancing frequency.

Now this is where the benefits of using our FDR strategy come to light. While estimated alphas decrease sharply as a result of transaction costs, half of them are still statistically and economically significant. It is worth noting that in the absence of skilled funds to invest in, the Hushen 300 ETF is advantageous for individual investors since it charges a fee that is less than 1% than the fees charged by actively managed funds.

(Insert Table 6)

Table 6 demonstrates the transaction cost-adjusted performance for institutional investors. After transaction costs, performance decreases slightly. However, for the 3-month rebalancing frequency, there is no evidence for abnormal returns. This suggests that a 3-month rebalancing frequency is too costly (since it results in a total of four occasions where rebalancing is needed for a given year).

Another observation worth noting in table 5 and table 6 is that it appears the FDR strategy dominates in terms of its efficacy when we increase the *p*-value threshold to what is specified in panel B ($1\% < p\text{-value} \leqslant 5\%$), we see a significant enhancement in alphas relative to the leading

[22] Trading ETFs in the stock market is similar as trading stocks. The transaction cost depends on the policy of different brokerage house (security companies in Chinese stock market). For more information about trading ETFs, please use the following URL link provided by Shanghai Stock Exchange (SSE): *http://edu.sse.com.cn/invesNetC/data/hai/products/ETF/*.

fund strategy. This leads us to conclude that applying too strict of a threshold (p-value $\leqslant$ 1%) may yield too few skilled mutual funds and a lack of diversification opportunities for investors. Increasing this threshold, however, yields more possible diversification opportunities without the significant threat of including "lucky" funds into the portfolio.

6.2 Trading Strategy for Leading Managers

In addition to examining performance persistence and developing trading strategies for mutual funds, we also entertain the possibility of whether our FDR strategy can be applied to fund managers. Doing so takes into account the possibility that fund managers switch employment and also tests whether superior fund performance comes as a result of the company as a whole or because of its manager.

At each month, the performance of each fund manager is measured as the equally-weighted average return of all funds that are under their management.[23] Then we follow exactly the same procedures as described in Section 6.1.

(Insert Table 7)

Similarly, when ranking fund managers on past estimated p-values, managers located in the extreme right tail of the p-value distribution exhibit performance persistence in the short-run. When compared to the performance persistence of top funds, the persistence of top fund managers is slightly weaker. For instance, in panel A of table 7, this portfolio shows significantly positive alphas only when it is rebalanced every 12 months. When we take the impact of luck into account, especially in panels B, C and D, our FDR strategy is superior to the leading manager strategy in terms of the alphas that it delivers. This outperformance in these three portfolios enables investors to diversify by adding more p-value portfolios (fund manager portfolios) and improve performance simultaneously. This findings is qualitatively similar with the findings we show for in tables 4 through 6 (for the individual funds).

[23] For funds with more than one manager, we have to assume that every fund manager expends the same amount of effort. Similarly, for managers who manage more than one fund simultaneously, we have to assume that they expend the same effort for each of the funds they manage.

(Insert Table 8)

As reported by table 8, after controlling for transaction costs, performance of these two strategies decreases significantly for individual investors. Only the portfolio that includes managers with past estimated *p*-values lower than 1% and with the 12-month rebalancing frequency can provide significantly positive alphas (shown in panel A). In panel D, the portfolio that rebalances four times a year generates a significantly negative monthly alpha of 0.61%. For the FDR strategy, the transaction cost-adjusted performance fares better most of the time.

(Insert Table 9)

Table 9 reports the transaction cost-adjusted performance for institutional investors. While the performance is somewhat reduced compared to table 7, institutional investors do benefit more relative to individual investors given the economies of scale of their trading.

6.3 Comparison with a Naive Return-Ranked Trading Strategy

In China, the majority of websites in the mutual fund industry, such as *Sina Finance*, *Howbuy.com* and *Cnstock.com*, provide performance rankings based on the past buy-and-hold return. Hence, in the last part of our test, we examine whether the return-based ranking method is better than our *p*-value-based ranking approach and whether the return-based ranking strategy can really benefit investors.

To be consistent with the previous tests in this paper, we divide all funds into 10 deciles based on the past 24-month buy-and-hold returns with the best funds in the 10^{th} decile and the worst funds in the 1^{st} decile. We then constructed 10 equally-weighted portfolios and rebalance them across the usual frequencies (3, 6, 12 and 24 months). Finally, we estimate the performance of these 10 portfolios using the four-factor model to see whether the portfolio that include funds with the best past buy-and-hold returns can provide a positive and significant alpha.

(Insert Table 10)

Table 10 reports the performance of the 10 past buy-and-hold return sorted portfolios. As shown in the second column, while the past loser (funds in the 1st decile) always underperform the other nine groups, the past winner (funds in the 10th decile) do not always provide the highest alpha. More importantly, almost none of these portfolios can generate a significant abnormal return beyond what is predicted by the four-factor benchmark. Hence, rankings based on these popularly advertised past buy-and-hold returns are not an ideal guide for investors trying to select mutual funds.

7. Conclusions

The Chinese mutual fund industry poses opportunities and risks for outside investors. Up until now, this industry is unchartered territory relative to the mutual fund industries of other developed markets. Academic literature on Chinese mutual funds collectively concludes, firstly, that fund managers cannot beat the market and, secondly, those that do beat the market are lucky and not truly skilled. In all, there is no roadmap for outside investors wishing to navigate its unique mutual fund industry despite China's growing economic importance in the world. Our paper presents a practical and exploitable roadmap for such investors and our findings are of importance to both practitioners and academicians alike. In summary, we illustrate the following.

Firstly, our FDR approach can accommodate, and be adjusted for, various investor-specific preferences such as holding horizons, rebalancing frequencies and diversification requirements. This is of particular importance to institutions that invest their clients' money into mutual funds and which must adhere to specific diversification requirements set by those clients.

Secondly, our FDR approach yields risk-adjusted returns (alphas) that are positive and significant. This finding, depending on the four-factor alpha *p*-value thresholds used to form portfolios, is quite robust across rebalancing frequencies and holds even after accounting for the actual transaction costs which individual or institutional investors must absorb when buying and selling mutual funds in China.

Thirdly, we show that our FDR approach can be used for both mutual fund companies as well as fund managers in order to distinguish luck from skill in overall fund performance. Treating mutual fund companies and mutual fund managers as two separate 'units' for empirical analysis is important because fund managers may switch employment between competing mutual fund companies. Decoupling the two is also important because fund companies may have 'star' managers who, relative to their team, disproportionately contribute to their company's success but who may, at any time, leave to join another company. From our FDR approach, we show stronger evidence of outperformance persistence at the fund manager level relative to the whole mutual fund company level. This indicates that individual fund managers who are 'stars' contribute disproportionately more to their company's outperformance in relation to their fund management team. From a managerial perspective, our findings support the adage that *employees are a company's greatest asset*. When we extend this to the Chinese mutual fund industry, however, we show that *fund managers are a mutual fund company's greatest asset*.

Finally, we evaluate our FDR approach against return-based methods for ranking mutual funds which have been popularized by various Chinese investment websites. We show that such return-based methods of ranking funds yields poor risk-adjusted returns relative to our FDR strategy. These websites may be providing rankings and buy/hold/sell recommendations that are consistent with the behaviors of feedback traders - this is because we show that past winners do not reliably yield future positive and significant four-factor alphas. Since these websites do not provide a formal method for distinguishing lucky funds from those that are truly skilled, their naive rankings of funds yield poor performance given that they may recommend "lucky" funds at any given point in time. Such funds inevitably experience mean reversion in their performance.

From a theoretical market efficiency point of view, our FDR approach shows that about 7% of all actively managed funds are skilled. This proportion of skilled funds is considerably higher than what is documented by others in developed markets. Future research can perhaps examine reasons for this and whether this manifests as a result of market inefficiencies which are not present in developed markets.

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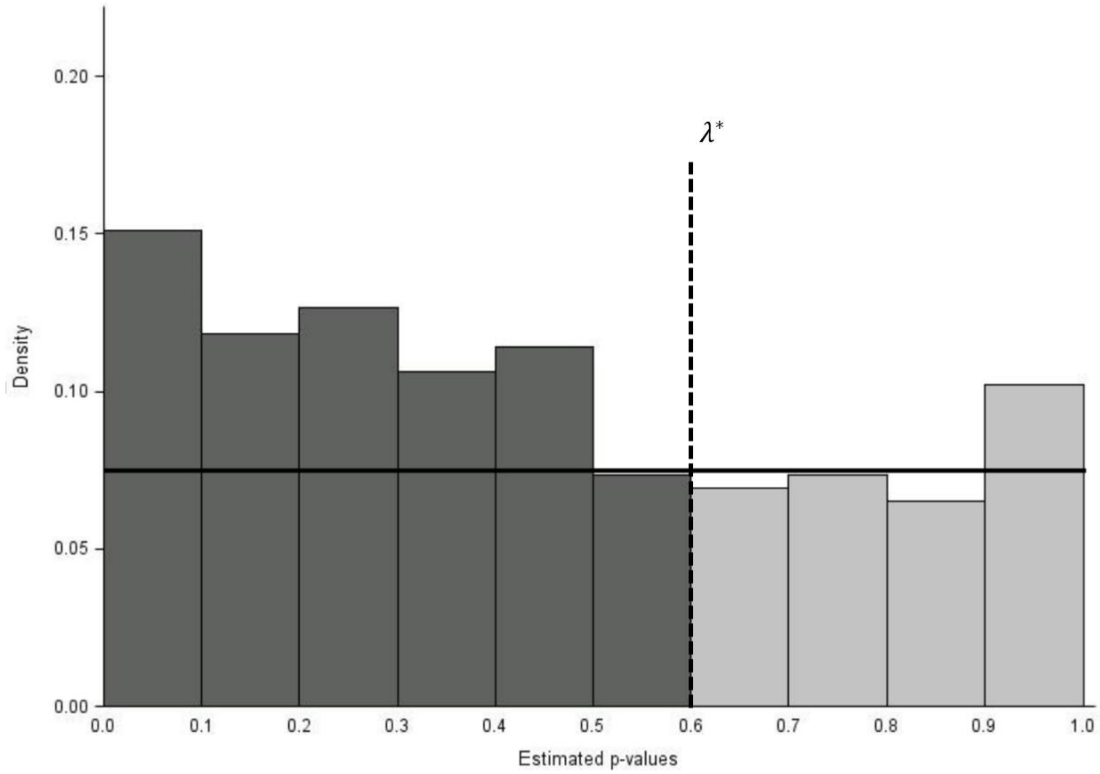
Figures and Tables

Figure 1
Histogram of *p*-values of funds' alpha



This figure shows the histogram of estimated *p*-values of all funds (245 funds in our sample) from January 2007 to December 2015. All the sample funds are stock funds and stock-dominated hybrid funds and must have at least two years of monthly return data. We first estimate the *p*-values of alphas for all individual funds under the null hypothesis that the estimated alphas are not different from zero (two-tailed *p*-value). We then plot all the *p*-values in this histogram. Alphas and the corresponding *p*-values are estimated by using Carhart (1997) four-factor model shown in equation (1).

Table 1

Aggregate Performance

Aggregate performance is estimated using the Carhart (1997) four-factor model. R_M-R_F, SMB, HML and MOM represent market, size, value and momentum factors, respectively. The regressions are based on the monthly returns of 245 stock funds and stock-dominated hybrid funds from January 2007 to December 2015. Sample funds must have at least two years of monthly return data. Figures in parentheses are *p*-values under the null hypothesis that the estimated coefficients are not different from zero. Panel A reports the performance of the equally-weighted portfolio which consists of all funds available at each month. Panel B reports the performance of the value-weighted portfolio that includes all available funds at each month (weights are based on total assets reported in December of the previous year).

Panel A: Equal-Weighted Portfolio						
	Alpha	R_M-R_F	SMB	HML	MOM	Adj. R^2
Coefficient	0.0013	0.7573	0.0901	-0.5012	0.1978	0.9486
	(0.4772)	(<.0001)	(0.0250)	(<.0001)	(<.0001)	
Panel B: Value-Weighted Portfolio						
	Alpha	R_M-R_F	SMB	HML	MOM	Adj. R^2
Coefficient	0.0007	0.7883	0.0309	-0.5094	0.1774	0.9530
	(0.6696)	(<.0001)	(0.4281)	(<.0001)	(<.0001)	

Table 2

Performance of Randomly Picked Portfolio

This table reports the performance of each randomly selected portfolio with a rebalancing frequency of 3, 6, 12 and 24 months, respectively. At the rebalance date, five funds are randomly selected to form an equally-weighted portfolio. R_M-R_F, SMB, HML and MOM represent market, size, value and momentum factors, respectively. The regressions are based on the monthly returns of randomly selected funds from January 2007 to December 2015. Sample funds must have at least two years of monthly return data. Figures in parentheses are *p*-values under the null hypothesis that the estimated coefficients are not different from zero.

Panel A: 3-Month Rebalance						
	Alpha	R_M-R_F	SMB	HML	MOM	Adj. R^2
Coefficient	0.0009	0.7427	0.0307	-0.5358	0.2241	0.9233
	(0.6644)	(<.0001)	(0.5217)	(<.0001)	(<.0001)	
Panel B: 6-Month Rebalance						
	Alpha	R_M-R_F	SMB	HML	MOM	Adj. R^2
Coefficient	0.0008	0.7455	0.0736	-0.4870	0.2000	0.9426
	(0.6608)	(<.0001)	(0.0774)	(<.0001)	(<.0001)	
Panel C: 12-Month Rebalance						
	Alpha	R_M-R_F	SMB	HML	MOM	Adj. R^2
Coefficient	0.0007	0.7406	0.1074	-0.4886	0.2713	0.9134
	(0.7649)	(<.0001)	(0.0409)	(<.0001)	(<.0001)	
Panel D: 24-Month Rebalance						
	Alpha	R_M-R_F	SMB	HML	MOM	Adj. R^2
Coefficient	0.0001	0.8042	0.1413	-0.3910	0.1426	0.9659
	(0.9441)	(<.0001)	(0.0013)	(<.0001)	(<.0001)	

Table 3
Impact of Luck on Fund Performance

Fund performance is measured using the Carhart (1997) four-factor model over the entire period from January 2007 to December 2015. 245 stock funds and stock-dominated hybrid funds are included. Sample funds must have at least two years of monthly return data. λ is the threshold to determine the proportion of zero-alpha funds. γ is the significance level. For the left tail, funds with significantly negative alphas ($S_{\gamma-}$) are decomposed into unlucky funds ($F_{\gamma-}$) and unskilled funds ($T_{\gamma-}$). Similarly, for the right tail, funds with significantly positive alphas ($S_{\gamma+}$) are decomposed into lucky funds ($F_{\gamma+}$) and skilled funds ($T_{\gamma+}$). Panels A, B and C report the impact of luck on Chinese mutual funds with $\lambda^* = 0.5$, 0.6 and 0.7, respectively.

Panel A: $\lambda^* = 0.5$									
	Left Tail				Right Tail				
γ	0.01	0.05	0.10	0.15	0.15	0.10	0.05	0.01	γ
$S_{\gamma-}$	0.41%	1.63%	4.08%	6.12%	16.33%	11.02%	6.94%	1.63%	$S_{\gamma+}$
$F_{\gamma-}$	0.38%	1.92%	3.84%	5.76%	5.76%	3.84%	1.92%	0.38%	$F_{\gamma+}$
$T_{\gamma-}$	0.03%	0.00%	0.24%	0.37%	10.57%	7.18%	5.02%	1.25%	$T_{\gamma+}$
Panel B: $\lambda^* = 0.6$									
	Left Tail				Right Tail				
γ	0.01	0.05	0.10	0.15	0.15	0.10	0.05	0.01	γ
$S_{\gamma-}$	0.41%	1.63%	4.08%	6.12%	16.33%	11.02%	6.94%	1.63%	$S_{\gamma+}$
$F_{\gamma-}$	0.39%	1.94%	3.88%	5.82%	5.82%	3.88%	1.94%	0.39%	$F_{\gamma+}$
$T_{\gamma-}$	0.02%	0.00%	0.20%	0.31%	10.51%	7.14%	5.00%	1.24%	$T_{\gamma+}$
Panel C: $\lambda^* = 0.7$									
	Left Tail				Right Tail				
γ	0.01	0.05	0.10	0.15	0.15	0.10	0.05	0.01	γ
$S_{\gamma-}$	0.41%	1.63%	4.08%	6.12%	16.33%	11.02%	6.94%	1.63%	$S_{\gamma+}$
$F_{\gamma-}$	0.40%	2.01%	4.01%	6.02%	6.02%	4.01%	2.01%	0.40%	$F_{\gamma+}$
$T_{\gamma-}$	0.01%	0.00%	0.07%	0.10%	10.31%	7.01%	4.93%	1.23%	$T_{\gamma+}$

Table 4
Trading Strategy (Funds)

This table reports the comparison between the leading fund trading strategy and false discovery rate (FDR) trading strategy, with respect to individual funds and without considering the impact of transaction costs. Number of funds represents the average number of funds that are included in our test portfolios across all holding periods. Skilled fund percent shows the average proportion of skilled funds ($T_{\gamma+}$) in all funds with significantly positive alphas ($S_{\gamma+}$). Alphas and *p*-values are estimated using the Carhart (1997) four-factor model. Funds are divided into five groups based on their *p*-values. For each group of funds, we have different rebalancing frequencies (3, 6, 12 and 24 month rebalances). Panels A through E demonstrate the results for each group. ***, ** and * denote significant level at 1%, 5% and 10% levels, respectively.

Panel A (*p*-value ≤ 1%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0042	0.0051	4	83%
6-month	0.0074**	0.0074***	3	82%
12-month	0.0107**	0.0063***	3	78%
24-month	0.0005	0.0002	3	92%
Panel B (1% < *p*-value ≤ 5%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0054**	0.0052*	7	60%
6-month	0.0045**	0.0062**	7	59%
12-month	0.0012	0.0057**	7	61%
24-month	-0.0017	0.0052**	7	60%
Panel C (5% < *p*-value ≤ 10%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0008	0.0033	8	43%
6-month	0.0028	0.0054**	6	39%
12-month	0.0030	0.0037*	7	44%
24-month	0.0013	0.0020	8	47%
Panel D (10% < *p*-value ≤ 20%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0024	0.0036	8	27%
6-month	0.0013	0.0040*	9	29%
12-month	0.0020	0.0043*	7	27%
24-month	0.0006	0.0029	6	27%
Panel E (20% < *p*-value ≤ 30%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0033	0.0043**	8	11%
6-month	0.0026	0.0050**	8	8%
12-month	0.0010	0.0055**	7	12%
24-month	0.0021	0.0028	8	18%

Table 5
Transaction Cost Adjusted Trading Strategy (Funds)
For Individual Investors

This table compares between the leading fund trading strategy and false discovery rate (FDR) trading strategy, with respect to individual funds after adjusting for transaction costs that individual investors are likely to incur. Number of funds represents the average number of funds that are included in our test portfolios across all holding periods. Skilled fund percent shows the average proportion of skilled funds ($T_{\gamma+}$) in all funds with significantly positive alphas ($S_{\gamma+}$). Alphas and *p*-values are estimated using the Carhart (1997) four-factor model. Funds are divided into five groups based on their *p*-values. For each group of funds, we have different rebalancing frequencies (3, 6, 12 and 24 month rebalances). Panels A through E demonstrate the results for each group. ***, ** and * denote significant level at 1%, 5% and 10% levels, respectively.

Panel A (*p*-value ≤ 1%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	-0.0025	-0.0008	4	83%
6-month	0.0041	0.0045*	3	82%
12-month	0.0091*	0.0048**	3	78%
24-month	-0.0004	-0.0005	3	92%
Panel B (1%< *p*-value ≤ 5%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	-0.0013	0.0007	7	60%
6-month	0.0012	0.0039	7	59%
12-month	-0.0005	0.0045*	7	61%
24-month	-0.0025	0.0046**	7	60%
Panel C (5% < *p*-value ≤ 10%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	-0.0059**	-0.0002	8	43%
6-month	-0.0005	0.0037*	6	39%
12-month	0.0013	0.0028	7	44%
24-month	0.0004	0.0016	8	47%
Panel D (10% < *p*-value ≤ 20%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	-0.0043**	0.0009	8	27%
6-month	-0.0020	0.0026	9	29%
12-month	0.0004	0.0036	7	27%
24-month	-0.0002	0.0025	6	27%
Panel E (20% < *p*-value ≤ 30%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	-0.0033	0.0024	8	11%
6-month	-0.0007	0.0041*	8	8%
12-month	-0.0007	0.0050**	7	12%
24-month	0.0013	0.0025	8	18%

Table 6
Transaction Cost Adjusted Trading Strategy (Funds)
For Institutional Investors

This table compares between the leading fund trading strategy and false discovery rate (FDR) trading strategy, with respect to individual funds after adjusting for transaction costs that institutional investors are likely to incur. Number of funds represents the average number of funds that are included in our test portfolios across all holding periods. Skilled fund percent shows the average proportion of skilled funds ($T_{\gamma+}$) in all funds with significantly positive alphas ($S_{\gamma+}$). Alphas and *p*-values are estimated using the Carhart (1997) four-factor model. Funds are divided into five groups based on their *p*-values. For each group of funds, we have different rebalancing frequencies (3, 6, 12 and 24 month rebalances). Panels A through E demonstrate the results for each group. ***, ** and * denote significant level at 1%, 5% and 10% levels, respectively.

Panel A (*p*-value ≤ 1%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0024	0.0034	4	83%
6-month	0.0065**	0.0065**	3	82%
12-month	0.0103**	0.0058**	3	78%
24-month	0.0002	0.0000	3	92%
Panel B (1% < *p*-value ≤ 5%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0036	0.0036	7	60%
6-month	0.0036*	0.0053**	7	59%
12-month	0.0007	0.0053**	7	61%
24-month	-0.0019	0.0050**	7	60%
Panel C (5% < *p*-value ≤ 10%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	-0.0010	0.0018	8	43%
6-month	0.0019	0.0047**	6	39%
12-month	0.0025	0.0033*	7	44%
24-month	0.0010	0.0019	8	47%
Panel D (10% < *p*-value ≤ 20%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0006	0.0021	8	27%
6-month	0.0004	0.0033	9	29%
12-month	0.0016	0.0039*	7	27%
24-month	0.0004	0.0027	6	27%
Panel E (20% < *p*-value ≤ 30%)				
Rebalance Frequency	Leading Fund Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Fund (%)
3-month	0.0015	0.0030	8	11%
6-month	0.0017	0.0043*	8	8%
12-month	0.0006	0.0051**	7	12%
24-month	0.0019	0.0026	8	18%

Table 7
Trading Strategy (Managers)

This table compares between the leading fund trading strategy and false discovery rate (FDR) trading strategy, with respect to individual fund managers and without considering the impact of transaction costs. Number of funds represents the average number of funds that are included in our test portfolios across all holding periods. Skilled fund percent shows the average proportion of skilled funds ($T_{\gamma+}$) in all funds with significantly positive alphas ($S_{\gamma+}$). Alphas and *p*-values are estimated using the Carhart (1997) four-factor model. Funds are divided into five groups based on their *p*-values. For each group of funds, we have different rebalancing frequencies (3, 6, 12 and 24 month rebalances). Panels A through E demonstrate the results for each group. ***, ** and * denote significant level at 1%, 5% and 10% levels, respectively.

Rebalance Frequency	Leading Manager Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Manager(%)
Panel A (p-value ≤ 1%)				
3-month	0.0009	0.0026	4	89%
6-month	0.0052	0.0078**	3	86%
12-month	0.0151**	0.0106***	2	87%
24-month	0.0058	0.0053	2	95%
Panel B (1% < p-value ≤ 5%)				
3-month	0.0039	0.0042	6	65%
6-month	0.0059*	0.0061*	6	65%
12-month	0.0047	0.0074**	5	64%
24-month	-0.0005	0.0049	4	67%
Panel C (5% < p-value ≤ 10%)				
3-month	0.0026	0.0010	6	53%
6-month	0.0017	0.0047*	4	42%
12-month	0.0011	0.0036*	4	46%
24-month	0.0016	0.0031	4	45%
Panel D (10% < p-value ≤ 20%)				
3-month	0.0006	0.0052*	7	35%
6-month	0.0018	0.0070***	7	35%
12-month	0.0026	0.0055**	6	42%
24-month	0.0008	0.0034	5	35%
Panel E (20% < p-value ≤ 30%)				
3-month	0.0035	0.0036	6	15%
6-month	0.0041	0.0044	5	11%
12-month	0.0047*	0.0055*	5	18%
24-month	0.0049*	0.0030	5	28%

Table 8
Transaction Cost Adjusted Trading Strategy (Managers) For Individual Investors

This table compares between the leading fund trading strategy and false discovery rate (FDR) trading strategy, with respect to individual fund managers after adjusting for transaction costs that individual investors are likely to incur. Number of funds represents the average number of funds that are included in our test portfolios across all holding periods. Skilled fund percent shows the average proportion of skilled funds ($T_{\gamma+}$) in all funds with significantly positive alphas ($S_{\gamma+}$). Alphas and *p*-values are estimated using the Carhart (1997) four-factor model. Funds are divided into five groups based on their *p*-values. For each group of funds, we have different rebalancing frequencies (3, 6, 12 and 24 month rebalances). Panels A through E demonstrate the results for each group. ***, ** and * denote significant level at 1%, 5% and 10% levels, respectively.

Rebalance Frequency	Leading Manager Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Manager(%)
Panel A (p-value ≤ 1%)				
3-month	-0.0058	-0.0035	4	89%
6-month	0.0019	0.0048	3	86%
12-month	0.0135**	0.0091**	2	87%
24-month	0.0049	0.0045	2	95%
Panel B (1% < p-value ≤ 5%)				
3-month	-0.0027	-0.0006	6	65%
6-month	0.0026	0.0038	6	65%
12-month	0.0031	0.0063**	5	64%
24-month	-0.0014	0.0042	4	67%
Panel C (5% < p-value ≤ 10%)				
3-month	-0.0040	-0.0032	6	53%
6-month	-0.0016	0.0029	4	42%
12-month	-0.0007	0.0026	4	46%
24-month	0.0007	0.0026	4	45%
Panel D (10% < p-value ≤ 20%)				
3-month	-0.0061**	0.0022	7	35%
6-month	-0.0016	0.0054**	7	35%
12-month	0.0009	0.0046*	6	42%
24-month	-0.0000	0.0030	5	35%
Panel E (20% < p-value ≤ 30%)				
3-month	-0.0032	0.0015	6	15%
6-month	0.0007	0.0034	5	11%
12-month	0.0030	0.0049*	5	18%
24-month	0.0041	0.0027	5	28%

Table 9
Transaction Cost Adjusted Trading Strategy (Managers)
For Institutional Investors

This table compares between the leading fund trading strategy and false discovery rate (FDR) trading strategy, with respect to individual fund managers after adjusting for transaction costs that institutional investors are likely to incur. Number of funds represents the average number of funds that are included in our test portfolios across all holding periods. Skilled fund percent shows the average proportion of skilled funds ($T_{\gamma+}$) in all funds with significantly positive alphas ($S_{\gamma+}$). Alphas and *p*-values are estimated using the Carhart (1997) four-factor model. Funds are divided into five groups based on their *p*-values. For each group of funds, we have different rebalancing frequencies (3, 6, 12 and 24 month rebalances). Panels A through E demonstrate the results for each group. ***, ** and * denote significant level at 1%, 5% and 10% levels, respectively.

Rebalance Frequency	Leading Manager Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Manager(%)
Panel A (p-value ≤ 1%)				
3-month	-0.0009	0.0008	4	89%
6-month	0.0043	0.0069**	3	86%
12-month	0.0147**	0.0102***	2	87%
24-month	0.0056	0.0051	2	95%
Panel B (1% < p-value ≤ 5%)				
Rebalance Frequency	Leading Manager Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Manager(%)
3-month	0.0021	0.0025	6	65%
6-month	0.0050	0.0053	6	65%
12-month	0.0043	0.0070**	5	64%
24-month	-0.0007	0.0047	4	67%
Panel C (5% < p-value ≤ 10%)				
Rebalance Frequency	Leading Manager Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Manager(%)
3-month	0.0008	-0.0006	6	53%
6-month	0.0008	0.0039	4	42%
12-month	0.0007	0.0032	4	46%
24-month	0.0014	0.0029	4	45%
Panel D (10% < p-value ≤ 20%)				
Rebalance Frequency	Leading Manager Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Manager(%)
3-month	-0.0012	0.0037	7	35%
6-month	0.0009	0.0062**	7	35%
12-month	0.0021	0.0051*	6	42%
24-month	0.0006	0.0032	5	35%
Panel E (20% < p-value ≤ 30%)				
Rebalance Frequency	Leading Manager Strategy Alpha	FDR Strategy Alpha	Number of Funds	Skilled Manager(%)
3-month	0.0017	0.0022	6	15%
6-month	0.0032	0.0037	5	11%
12-month	0.0042	0.0051*	5	18%
24-month	0.0047*	0.0029	5	28%

Table 10

Persistence across Deciles (Return Sorted)

Panel A 3-Month Rebalance		
Decile	Alpha	P-Value
1	-0.0014	0.4302
2	0.0003	0.8824
3	0.0007	0.7075
4	0.0022	0.2974
5	0.0008	0.6794
6	0.0021	0.2818
7	0.0015	0.4715
8	0.0003	0.8891
9	0.0011	0.5698
10	0.0021	0.3203
Panel B 6-Month Rebalance		
Decile	Alpha	P-Value
1	-0.0006	0.7811
2	0.0022	0.2148
3	-0.0002	0.9082
4	-0.0005	0.8208
5	0.0004	0.8263
6	0.0039	0.0842*
7	0.0023	0.2926
8	-0.0001	0.9565
9	0.0013	0.4919
10	0.0016	0.4369
Panel C 12-Month Rebalance		
Decile	Alpha	P-Value
1	-0.0014	0.5286
2	0.0034	0.0854*
3	0.0023	0.2126
4	0.0001	0.9625
5	0.0019	0.3371
6	0.0013	0.5604
7	-0.0001	0.9629
8	-0.0004	0.8070
9	0.0021	0.2960
10	0.0022	0.2571
Panel D 24-Month Rebalance		
Decile	Alpha	P-Value
1	-0.0050	0.0288**
2	-0.0011	0.6115
3	-0.0024	0.2181
4	-0.0014	0.4804
5	-0.0005	0.8199
6	-0.0002	0.9091
7	0.0006	0.7516
8	0.0005	0.8139
9	0.0006	0.8090
10	0.0002	0.9280